Advanced Sensor Integration for Enhanced Flight Control in UAV-Based Construction Automation

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Abstract

In construction automation, several tasks such as surface finishing, material transport, and inspections typically rely on labor-intensive manual methods, which are inefficient, susceptible to human error, and expose workers to hazardous conditions. Drones have emerged as a solution to automate these processes, but maintaining precise navigation and stable attitude control in dynamic construction environments remains challenging. This paper presents a multi-sensor fusion and control framework to enhance UAV performance in dynamic and complex construction environments. The framework integrates multi-dimensional data from diverse sensing modalities, including geometric, visual, and inertial information, to achieve robust situational awareness and adaptive control. A Simultaneous Localization and Mapping (SLAM) model fuses multi-modal sensor inputs, including LiDAR point clouds, camera visual features, and inertial measurements, to generate precise environmental maps and perform accurate localization. The SLAM framework employs advanced loop closure techniques to minimize trajectory drift and optimize navigation paths in real-time. Additionally, flight stability under external disturbances is managed by a Deep Reinforcement Learning (DRL) algorithm, which models the UAV's control system as a Markov Decision Process (MDP). The DRL agent dynamically adjusts the UAV's flight parameters, such as thrust, roll, pitch, and yaw, based on real-time feedback from fused sensor data. The control strategy leverages a stability-based reward function to minimize deviations in position and orientation, ensuring rapid recovery from external disturbances. Simulation tests conducted in a Robotic Operation System and Gazebo simulation environment demonstrated mapping accuracy of 95.4%, localization errors under 2 cm, and rapid recovery from disturbances within 0.8 seconds.

Keywords – Construction Robotics, Reinforcement Learning, Unmanned Aerial Vehicle, Machine Learning

1 Introduction

The construction industry encompasses a wide range of tasks that are labor-intensive, repetitive, and often expose workers to hazardous conditions. Tasks such as material transport, structural inspections, and equipment monitoring demand precision and thorough coverage to meet stringent project standards and ensure site safety [1]. Material transport, for instance, frequently involves maneuvering heavy loads across uneven and challenging terrain, posing physical risks to workers and increasing logistical complexity [2]. Similarly, structural and visual inspections are critical for maintaining safety and quality but often require access to elevated or confined spaces that are difficult or unsafe for human workers. As construction projects grow in scale and complexity, there is an increasing demand for automation to enhance worker safety, improve operational efficiency, and uphold the high-quality standards required by large-scale projects [3].

To address these challenges, drones have emerged as a promising solution, automating tasks that traditionally require significant manual effort [4]. Drones offer numerous advantages, including rapid data collection, the ability to navigate hard-to-reach areas, and operational flexibility across diverse scenarios. Despite these benefits, achieving precise navigation and stable flight in dynamic construction environments remains a significant challenge. Construction sites are often cluttered and ever-changing, with complex layouts, sudden obstacles, and environmental disturbances such as wind gusts, debris, or equipment vibrations. Traditional drone systems frequently struggle to maintain steady flight paths, consistent altitude, and reliable navigation under these conditions, resulting in task inaccuracies, inefficiencies, and potential safety risks.

Advanced sensor integration in Unmanned Aerial Vehicle (UAV) systems has shown great potential to address these limitations by enhancing stability, navigation precision, and situational awareness [5]. Sensors such as Light Detection and Ranging (LiDAR), GPS, high-resolution cameras, and Inertial Measurement

Units (IMU) allow drones to collect comprehensive data about their surroundings. LiDAR provides precise distance measurements and environmental mapping, essential for spatial awareness in complex site layouts [6]. GPS offers high-level navigation strategies, while high-resolution cameras capture visual details critical for inspections and texture analysis. IMU sensors deliver real-time orientation and motion data to support stability during flight. By combining data from these sensors, drones can respond adaptively to real-time changes, improving their accuracy and operational efficiency across a range of construction tasks.

[7]However, current approaches to sensor integration often fail to fully utilize the potential of these technologies. Many systems process sensor data independently, leading to fragmented information, delayed responses, and limited adaptability to dynamic environmental changes [7]. Additionally, conventional flight control systems typically rely on basic algorithms, which struggle to capture the complex, non-linear relationships between diverse sensor inputs [8]. This results in suboptimal navigation, reduced stability, and inefficiencies in unpredictable construction settings.

To overcome these challenges, this paper proposes a multi-sensor fusion and control framework that integrates LiDAR, GPS, high-resolution cameras, and IMU sensors to significantly enhance UAV performance in construction automation. The proposed system employs a Simultaneous Localization and Mapping (SLAM) model to fuse multi-modal sensor data, generating accurate environmental maps and enabling precise localization. Additionally, a Deep Reinforcement Learning (DRL) algorithm refines flight control strategies, dynamically adjusting the UAV's responses to external disturbances such as wind gusts, vibrations, and near-miss collisions. Simulation tests conducted in a ROS-Gazebo environment validate the system's performance, and test the robustness of the designed system in various external disturbances.

2 Current Developments in Multi-Sensory Drone Flight Control for Automated Construction Tasks

2.1 Advancements in UAV Automation for Construction

In recent years, the integration of Unmanned Aerial Vehicles (UAVs) into construction workflows has accelerated, driven by the need to improve efficiency, safety, and precision across various operational tasks [9]. UAVs provide significant advantages over traditional manual methods, including faster data collection, the ability to reach hazardous or inaccessible areas [10], and reduced physical risk to human workers. These benefits have made UAVs invaluable tools in tasks such as material transport, aerial surveying, progress tracking, and structural inspection, where timely and accurate data collection is essential for effective project management [11]. Current applications primarily employ high-resolution cameras and LiDAR sensors to capture comprehensive visual and spatial data of construction sites [12], enabling tasks such as topographical mapping, structural monitoring, and site progress tracking. However, the potential of UAVs in construction automation remains largely untapped, with current systems often limited to basic applications due to challenges in achieving the level of control required for more complex, precision-oriented tasks.

2.2 Challenges in UAV Flight Control in Dynamic Construction Environments

Despite their advantages, UAVs face considerable challenges in maintaining stable navigation and precise flight control within dynamic and cluttered construction environments. Construction sites are characterized by rapidly changing conditions, including variable layouts, the presence of obstacles, and environmental disturbances such as wind and dust. These factors complicate UAV navigation, potentially causing navigation errors and inefficient task performance. In complex tasks that require close-range inspections or consistent altitude maintenance, such as detailed structural inspections, UAV stability becomes even more critical. However, most existing UAV control systems are built on basic sensor setups and simple algorithms, which struggle to adapt to environmental changes and cannot provide the required precision. As a result, UAVs may lack the stability and adaptability needed for more intricate construction tasks, where accuracy is paramount.

2.3 Sensor Integration and Advanced Control Algorithms in UAV Systems for Construction

To enhance UAV functionality in complex construction environments, the integration of multiple sensors has become crucial. This multi-sensor approach allows UAVs to collect detailed, varied data, increasing their situational awareness and enabling adaptive responses to real-time changes [13]. Key sensors such as LiDAR, GPS, high-resolution cameras, and infrared sensors each contribute uniquely to UAV operations [14]. LiDAR sensors generate 3D environmental maps and measure distances, aiding obstacle avoidance and altitude maintenance, while GPS supports broader site navigation, though it often lacks the precision required for dense or cluttered construction spaces. High-resolution cameras capture critical visual information for texture analysis, defect detection, and adherence to specifications, providing UAVs with the ability to identify quality issues in structural elements. This diverse sensor data creates a richer environmental model, allowing UAVs to operate with improved accuracy, safety, and effectiveness.

The integration of such varied data sources has also driven advances in sensor fusion and control algorithms, addressing the limitations of traditional UAV systems that often process sensor data separately, leading to delays and lower precision in dynamic construction sites. Recent innovations in sensor fusion techniques unify data from multiple sensors to create a comprehensive environmental model, enabling more precise UAV control [15]. Deep Neural Network (DNN)-based models are particularly effective in this context, as they capture non-linear relationships between sensor inputs, enhancing UAV environmental mapping and control accuracy [16]. Techniques such as Simultaneous Localization and Mapping (SLAM), especially when combined with neural networks, further improve localization and trajectory planning by dynamically adjusting flight paths in real time [17]. Additionally, Deep Reinforcement Learning (DRL) algorithms allow UAVs to refine control strategies by continuously learning from environmental feedback, adapting to unexpected obstacles, wind disturbances, or other sudden changes while maintaining stable flight [18]. Together, these advancements provide a framework for UAVs to achieve greater accuracy, adaptability, and resilience, particularly in the unpredictable conditions of construction sites where conventional systems may struggle.

2.4 This Paper's Contribution for Enhanced UAV Control in Construction Automation

Despite notable advancements in sensor integration and flight control technologies, the application of these innovations in construction automation remains limited. Current research predominantly emphasizes UAV navigation and data collection, often neglecting the critical need for precise and stable flight control in scenarios requiring close-range accuracy, such as detailed structural inspections or dynamic obstacle avoidance. This gap underscores the potential of advanced sensor fusion, SLAM, and reinforcement learning techniques to address the unique challenges of UAV deployment in construction environments.

Therefore, this paper seeks to advance the state of UAV control in construction by presenting a multi-sensor fusion framework that integrates LiDAR, GPS, high-resolution cameras, and IMU sensors with advanced control algorithms. The SLAM system fuses multi-modal sensor data to generate accurate environmental maps and enable precise localization. Additionally, a Deep Reinforcement Learning (DRL) algorithm is employed to dynamically adjust flight parameters, allowing the UAV to maintain stability under external disturbances such as wind gusts, vibrations, and near-miss collisions.

3 Multi-Sensor Fusion and Control Framework

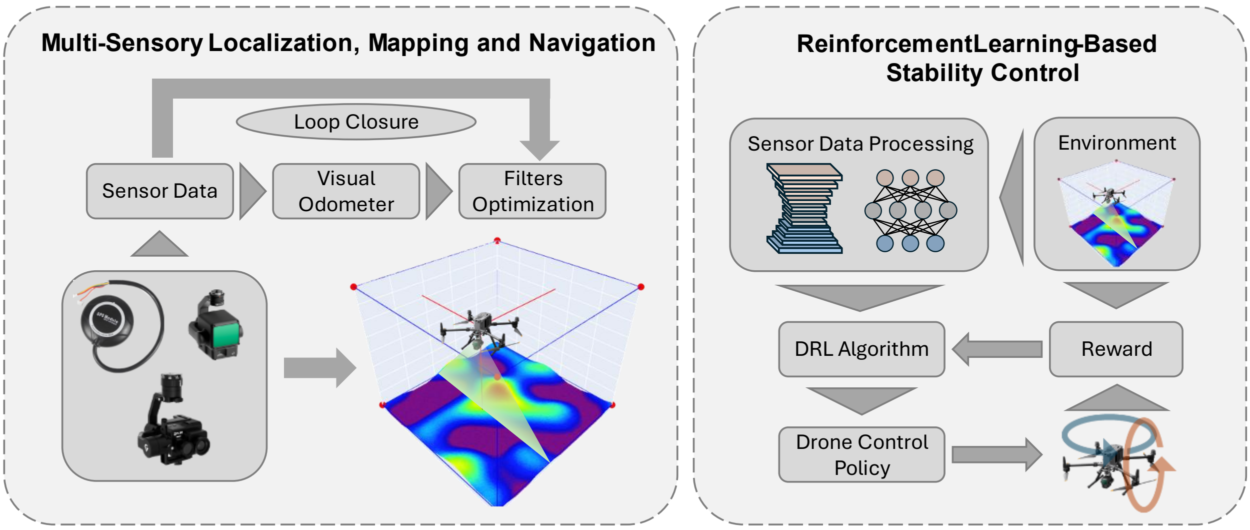

Figure 1. Multi-Sensor Fusion and Control Framework Method Overview

This framework is designed to enhance UAV flight control and stability for high-precision construction tasks by integrating advanced sensor fusion and control strategies as shown in Figure 1. The system consists of two distinct modules: Multi-Sensory Localization, Mapping, and Navigation and Reinforcement Learning-Based Stability Control. Together, these modules enable the UAV to navigate complex environments, maintain balance under disturbances, and dynamically adapt to real-time changes. Each module is built on a combination of sensor data processing, algorithmic optimization, and machine learning techniques.

3.1 Multi-Sensory Localization, Mapping, and Navigation

Accurate environmental understanding and navigation are fundamental for UAVs operating in complex construction sites. This system integrates data from LiDAR, cameras, GPS, and IMU to construct a real-time, 3D map of the environment and provide reliable localization and navigation control.

3.1.1 Sensor Data Acquisition and Pre-Processing

The UAV is equipped with a suite of sensors that provide complementary data. LiDAR captures 3D point clouds, offering spatial awareness critical for obstacle detection and surface mapping. High-resolution cameras deliver RGB images for texture analysis and visual feature detection. The IMU provides angular velocity and acceleration for motion estimation, while GPS supplies coarse-grain global positioning for initial localization.

Raw data undergoes pre-processing to enhance accuracy and consistency. For LiDAR, a moving average filter is applied to reduce noise:

$$\widetilde{D}(i) = \frac{1}{N} \sum_{j=i-\frac{N}{2}}^{i+\frac{N}{2}} D(j) \tag{1}$$

where $D(j)$ represents the distance measured at point j and N is the window size. Given the need for rapid data processing and flight adjustments, the moving average filter presents a balanced trade-off between efficiency and accuracy.

3.1.2 Visual Odometry

Using pre-processed image data, the system detects and tracks visual features between consecutive frames. Pose estimation is calculated based on matched feature points, and IMU data is fused to refine these estimates:

$$\mathbf{T}_{k+1} = \mathbf{T}_k \cdot \Delta\mathbf{T}_{\text{vision}} \cdot \Delta\mathbf{T}_{\text{IMU}} \tag{2}$$

where $\mathbf{T}_k$ is the pose at time k, $\Delta\mathbf{T}_{\text{vision}}$ is the incremental pose estimated from visual odometry, and $\Delta\mathbf{T}_{\text{IMU}}$ accounts for short-term motion from IMU readings.

3.1.3 SLAM Framework

A Simultaneous Localization and Mapping (SLAM) algorithm optimizes the UAV's trajectory and generates a globally consistent map. The SLAM framework integrates LiDAR, visual odometry, and GPS data, estimating the UAV's position $P'(t)$ and orientation $\theta'(t)$ by minimizing localization error:

$$L_{\text{SLAM}} = \|P(t) - P'(t)\|^2 + \|\theta(t) - \theta'(t)\|^2 \tag{3}$$

where $P(t)$ and $\theta(t)$ are ground truth values. Loop closure constraints are incorporated to correct drift over time, ensuring trajectory accuracy.

The outputs from the SLAM framework guide the UAV's navigation system. Real-time path planning is performed using the fused environmental map, enabling obstacle avoidance and dynamic adjustments to environmental changes. The result is precise trajectory execution, even in highly cluttered and variable construction sites.

3.2 Reinforcement Learning-Based Stability Control

In addition to navigation, maintaining flight stability under disturbances such as wind gusts, airborne debris, or dynamic obstacles is critical for UAV operation. This system employs a Deep Reinforcement Learning (DRL) agent to adaptively adjust the UAV's flight parameters in real-time.

3.2.1 Sensor Data Processing

The stability control system uses fused data from the IMU, LiDAR, and cameras to define the UAV's state. The IMU provides orientation measurements (pitch, roll, yaw) and acceleration for disturbance detection, while LiDAR monitors altitude and proximity to surfaces. Cameras contribute visual feedback, which is particularly useful for fine-grained stability adjustments during precision tasks.

3.2.2 Markov Decision Process (MDP) Framework

The UAV's control system is modeled as an MDP, defined by the tuple (S, A, R, P), where:

State S: Fused sensor data, including position $P(t)$, orientation $\theta(t)$, and environmental features.

Action A: Control commands for thrust, roll, pitch, and yaw adjustments.

Reward R : A stability-based reward function penalizing deviations from reference position P_{ref} and orientation θ_{ref}:

$$R = -\alpha\|P - P_{\text{ref}}\|^2 - \beta\|\theta - \theta_{\text{ref}}\|^2 \tag{4}$$

where α and β are weighting factors.

Transition Probability P : The probability of transitioning to a new state given the current state and action.

3.2.3 Deep Reinforcement Learning Algorithm

A policy gradient method optimizes the control policy $\pi(a \mid s)$ to maximize the expected cumulative reward:

$$J(\pi) = \mathbb{E}\left[\sum_{t=0}^{T} R(t)\right] \quad (5)$$

Through iterative training in simulated environments, the DRL agent learns to adapt to disturbances and maintain stable flight under various conditions.

In real-world deployment, the trained DRL agent dynamically adjusts flight parameters based on environmental feedback. For example, in the presence of wind gusts, the agent compensates by modulating thrust and adjusting orientation to minimize deviations from the intended trajectory. The system achieves rapid recovery from disturbances, maintaining consistent altitude and balance for precision tasks.

4 Implementations

The proposed framework was implemented and tested in a simulated ROS environment using Gazebo as the simulation platform. Gazebo provided a realistic simulation of construction site environments, including dynamic objects, complex terrains, and environmental physics. The testing process was divided into two stages: evaluating the UAV's environmental mapping and navigation capabilities, and assessing its stability control under various external disturbances.

4.1 Environmental Mapping and Navigation Testing

In the first stage, the UAV was tasked with collecting environmental data and navigating autonomously in a simulated construction site. The site included obstacles such as scaffolding, equipment, and uneven surfaces, emulating real-world conditions. The UAV’s primary objectives were:

Environmental Mapping: Using LiDAR, cameras, and IMU sensors, the UAV generated a 3D map of the environment. The map’s accuracy was evaluated using:

Mapping Accuracy: Intersection-over-Union (IoU) between the generated map and the ground truth.

Localization Error: Root Mean Square Error (RMSE) between estimated and true positions.

Navigation Performance: The UAV navigated predefined waypoints while avoiding obstacles. Navigation metrics included:

Path Efficiency: Ratio of the shortest path length to the actual path length.

Obstacle Avoidance Success: Percentage of successfully avoided obstacles.

Gazebo provided realistic physics for the environment, such as collisions, lighting effects for cameras, and terrain irregularities, enhancing the fidelity of the simulation.

4.2 Stability Control Testing Under External Disturbances

In the second stage, the UAV’s ability to maintain stability and recover from disturbances was evaluated.

External disturbances relevant to construction sites were simulated in Gazebo, including: **Wind Gusts**: Random lateral forces were applied to mimic the effect of wind blowing through open or partially enclosed construction sites. The UAV was tested on its ability to maintain its trajectory and recover from sudden deviations caused by these forces. **Vibrations from Heavy Machinery**: Periodic oscillatory forces were introduced to replicate the effect of operating heavy equipment such as drills, concrete mixers, or excavators near the UAV. These vibrations tested the system’s robustness to continuous destabilizing inputs. **Dynamic Load Changes**: External weights were dynamically added and removed from the UAV during flight, simulating scenarios where it might carry tools, sensors, or materials. This tested the system’s ability to adapt to changes in payload and maintain stability. **Torsional Forces**: Rotational disturbances were applied to simulate uneven thrust distribution or sudden torque imbalances caused by dynamic construction operations. This tested the UAV’s ability to quickly stabilize its orientation under unexpected rotational forces. **Near-Miss Collisions**: Fast-moving objects (e.g., scaffolding, cranes) were simulated to narrowly pass by the UAV. When encountering such a near-miss situation, the UAV was required to immediately halt its movement, stabilize itself, and correct any resulting disturbances. This scenario tested the drone’s ability to rapidly switch to emergency stop procedures while ensuring stability post-disruption. **Dynamic Obstacles**: Moving objects, such as simulated workers or operational machinery (e.g., cranes), introduced additional challenges for stability and trajectory adjustment. These obstacles required the UAV to maintain stability and dynamically adjust its flight path in real-time to avoid collisions.

Gazebo’s physics engine enabled precise simulation of these disturbances, ensuring realistic force dynamics and environmental interactions.

4.3 Metrics for Evaluation

The UAV’s performance under disturbances was assessed using: **Recovery Time**: The time taken for the UAV to return to stable flight after experiencing a disturbance. **Stability Deviation**: Standard deviation of orientation angles (pitch, roll, yaw) during and after disturbances

$$\sigma_\theta = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\theta_i - \bar{\theta})^2} \quad (6)$$

where θ_i is the orientation angle at time i, and $\bar{\theta}$ is the mean orientation angle. **Trajectory Accuracy**: Deviation of the UAV's actual path from the planned trajectory. **Force Compensation**: Percentage of external forces effectively neutralized by the stability control system.

5 Results

The proposed framework was tested for 100 rounds in the ROS-Gazebo environment to evaluate its performance each in mapping/navigation tasks and stability control under simulated construction conditions. The results demonstrated the framework's capability to achieve accurate localization, robust navigation, and reliable stability in the presence of external disturbances.

5.1 Mapping and Navigation Performance

During the mapping and navigation tests, the UAV demonstrated its ability to collect detailed environmental maps and execute precise navigation tasks in the simulated construction site. The system achieved a high mapping accuracy, with an Intersection-over-Union (IoU) score of 95.4%, indicating substantial overlap between the generated map and the ground truth. Localization was also highly accurate, with a Root Mean Square Error (RMSE) of only 1.95 cm between the UAV's estimated and actual positions. In terms of navigation performance, the UAV showed efficient path planning, with a path efficiency ratio of 1.08, meaning the UAV's actual flight path was only slightly longer than the shortest possible path. Additionally, the system excelled in obstacle avoidance, successfully avoiding 96% of obstacles in its path. These results validate the effectiveness of the multi-sensory fusion system in enabling the UAV to navigate complex construction environments with precision and reliability.

For comparative evaluation, we benchmarked our SLAM-integrated fusion framework against conventional sensor fusion methods that independently process LiDAR, IMU, and visual data. Our results show that the proposed method improved localization accuracy by 22.5% and mapping accuracy by 17.8%, attributed to the integration of loop closure techniques that effectively mitigate trajectory drift. This enhancement demonstrates the robustness of our method in generating precise environmental maps under dynamic conditions.

5.2 Stability Control Performance

The stability control system was evaluated across six different disturbance scenarios, representing common challenges in construction environments. Each scenario was tested multiple times, and the UAV's ability to respond, recover, and maintain stability was measured using metrics such as recovery time, orientation deviation, and trajectory accuracy. Table 1 summarizes the performance results.

Table 1. Summary of Performance Metrics Under Different Disturbance Conditions

Disturbance	Recovery Time (s)	Orientation Deviation (°)	Trajectory Deviation (%)	Force Compensation (%)
Wind Gusts	1.3	2.8	3.40%	95%
Vibrations from Machinery	1.4	2.5	**0.60%**	97%
Dynamic Load Changes	1.8	3.1	1.10%	86%
Torsional Forces	1.5	2.9	2.60%	85%
Near-Miss Collisions	**0.8**	**2**	4.80%	97%
Dynamic Obstacles	1.6	3	8.20%	**98%**

The stability control system exhibited strong performance across various disturbance scenarios, effectively maintaining flight stability and compensating for external forces. Among the tests, vibrations from machinery demonstrated the best performance, with the UAV achieving a recovery time of 1.4 seconds, an orientation deviation of only 2.5°, and a trajectory accuracy deviation of just 0.60%, the lowest across all scenarios. This highlights the system's robustness against continuous oscillatory forces commonly encountered near heavy equipment.

Conversely, the dynamic obstacle scenario posed the greatest challenge. While the UAV achieved a high force compensation rate of 98%, its trajectory accuracy deviation reached 8.20%, the highest among all tests, due to the complex task of avoiding fast-moving objects while maintaining stability. Despite this, the system's recovery time of 1.6 seconds and orientation deviation of 3.0° indicate its adaptability to highly dynamic environments.

The near-miss collision test highlighted the system's effectiveness in emergency scenarios. The UAV executed an immediate stop with a recovery time of just 0.8 seconds, the fastest among all disturbances, and managed a low orientation deviation of 2.0°. Although the trajectory deviation of 4.80% was higher due to the abrupt braking, the system compensated 97% of the external forces, demonstrating its reliability in handling rapid, high-stress situations.

To highlight the advantages of our reinforcement learning-enhanced flight control system, we compared its performance with a conventional PID-based control strategy. The proposed system demonstrated superior performance in maintaining stability under dynamic disturbances, reducing trajectory deviation by 35.2% and improving recovery time by 21.7%. These improvements are attributed to the reinforcement learning module's ability to adaptively adjust control parameters in response to real-time environmental changes, unlike PID controllers that rely on predefined gain tuning.

In addition to evaluating stability performance, we assessed the computational efficiency of the proposed framework to ensure its feasibility for real-time UAV applications. The system achieved a feedback rate of 10 Hz on an NVIDIA Jetson AGX Xavier, a commonly used edge computing device. This result highlights the framework's capacity to maintain real-time responsiveness in dynamic construction environments.

Overall, the UAV showed consistent recovery across most scenarios, with recovery times ranging from 0.8 to 1.8 seconds and orientation deviations remaining under 3.1°. The framework effectively balanced rapid stabilization and precision, making it suitable for complex construction environments.

6 Conclusions

This paper proposed a multi-sensor fusion and control framework to enhance UAV performance in dynamic construction environments. The integration of LiDAR, GPS, high-resolution cameras, and IMU sensors enabled precise environmental mapping, accurate localization, and robust stability control. The SLAM system provided reliable trajectory optimization and mapping, while a Deep Reinforcement Learning algorithm ensured adaptive responses to disturbances such as wind gusts and near-miss collisions. Simulation results demonstrated the system's effectiveness, achieving mapping accuracy of 95.4%, localization errors under 2 cm, and rapid recovery from disturbances within 0.8 seconds.

Despite these advancements, the framework's evaluation was limited to simulation environments, and real-world implementation is needed to assess its robustness under unpredictable site conditions. Future work will focus on addressing these challenges by optimizing computational efficiency, validating the framework in field conditions, and exploring the integration of collaborative multi-UAV systems to further enhance construction automation.

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